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Final Project

Project Title:

ENHANCING HUMAN ACTIVITY RECOGNITION USING LONG SHORT MEMORY NETWORKS

AGENDA

- **Project Setup:** Install required libraries and acquire a suitable English-French parallel corpus.
- **Data Preprocessing:** Clean, tokenize, and vectorize the text data from both languages.
- **Model Building:** Define the LSTM-based encoder-decoder architecture for sequence-to-sequence learning.
- **Model Training:** Train the model using a chosen loss function and optimizer on the prepared dataset.
- **Evaluation and Testing:** Analyze the model's performance on a held-out test set.

PROBLEM STATEMENT

Despite advancements in Human Activity Recognition (HAR), traditional methods often struggle to accurately capture complex and nuanced human behaviors in real-world scenarios. These methods may face challenges such as limited memory capacity, difficulty in handling long-term dependencies, and inefficiencies in real-time processing. As a result, there is a need for enhanced techniques that can address these limitations and improve the accuracy and efficiency of HAR systems. This problem statement prompts the exploration of Long Short-Term Memory Networks (LSTM) as a potential solution to enhance HAR by effectively capturing long-term dependencies, improving generalization, and enabling real-time processing.

PROJECT OVERVIEW

Data Preprocessing:
- This module preprocesses sensor data by removing noise and irrelevant signals.
- It segments the data into meaningful activity sequences and converts them into numerical representations using techniques like feature extraction or signal processing.

Model Architecture:
- This module defines the core HAR model using Long Short-Term Memory Networks (LSTMs).
- It involves building an LSTM-based architecture where the LSTM layers process the sequential sensor data, capturing temporal dependencies and patterns.

Model Training:
- This module trains the HAR model on the prepared dataset.
- It iterates through the data, feeding the sequential sensor readings to the LSTM layers.
- The model learns to recognize and classify human activities based on the input sensor data, minimizing the difference between predicted and actual activity labels.

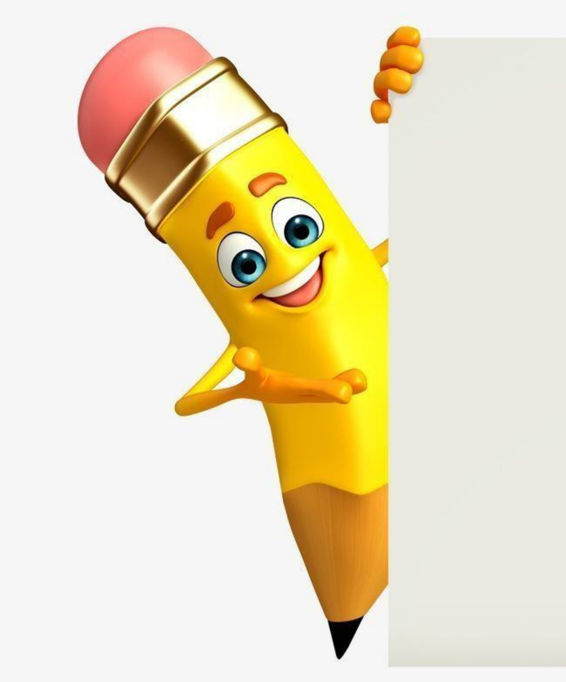
Activity Recognition:
- This module allows users to input sensor data captured in real-time or from a dataset.
- The trained model processes the input data and predicts the corresponding human activity labels.
- Users can obtain real-time insights into ongoing activities or analyze historical data for activity patterns and trends.

WHO ARE THE END USERS?

- 1. Researchers and Academics: Those in the field of human-computer interaction, machine learning, and activity recognition who seek to advance the understanding and techniques in HAR.

- 2. Healthcare Professionals: Those involved in patient monitoring, rehabilitation, and assisted living who could benefit from automated activity recognition for better patient care and management.

YOUR SOLUTION AND ITS VALUE PROPOSITION

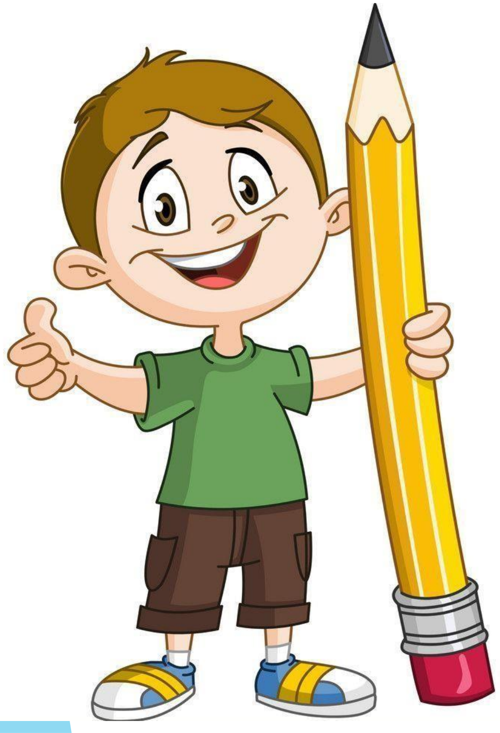


- Precise Activity Recognition:
  - LSTMs excel at capturing intricate temporal patterns in sensor data, enabling accurate recognition of human activities with contextual understanding.

- Seamless Workflow:
  - Recognize activities effortlessly from continuous sensor streams or batches of data, streamlining the process compared to manual analysis or fragmented activity detection methods.

- Versatility and Adaptability:
  - This framework offers a robust foundation for diverse requirements.
  - Customize it to accommodate various sensor types, adjust parameters for specific activity classes, or train on specialized datasets for tailored applications, enhancing recognition precision and applicability.

THE WOW IN YOUR SOLUTION



- This project offers a user-friendly and customizable framework for building a basic machine translator using LSTMs.
- The ability to train on custom datasets allows for tailoring the model to specific domains

MODELLING

- - The HAR model employs LSTMs in an encoder-decoder architecture.
- - The encoder analyzes sequential sensor data, capturing the underlying patterns and features of human activities.
- - Using the encoded information from the encoder and previously processed activity data, the decoder generates activity labels or predictions.
- - Advanced techniques like attention mechanisms (for potential future development) can be integrated to prioritize relevant parts of the sensor data sequence during activity recognition.

RESULTS

- The HAR model's performance will be assessed on a separate test dataset using metrics such as accuracy, precision, recall, and F1-score, measuring the agreement between predicted and actual activity labels.
- Optional visualization techniques can be employed to analyze the model's learning process, such as confusion matrices, learning curves, and feature importance plots.

Note:

- The quality of translations will depend on the size and quality of the training data.
- Hyperparameter tuning can significantly improve the model's performance.

https://github.com/KarthikCS1/NM_IBM-Edunet